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14. ABSTRACT Brain Computer Interfaces (BCIs) show great potential in allowing humans to interact with computational environments in a synergistic and complementary way. This project focused on acquiring a mobile robotic agent platform that can be used to explore these interfaces for a variety of real-world tasks and environments of interest to the Army. It aims to extend our current work, for creating systems enabling mutually-derived situation awareness which use BCI to synergistically couple human expertise and computational intelligence. This DURIP extends this work by providing a test environment where the human control of a robot agent can be experimentally validated in					
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Report Title

Final Report: Brain Computer Interfaces for Enhanced Interactions with Mobile Robot Agents

ABSTRACT

Brain Computer Interfaces (BCIs) show great potential in allowing humans to interact with computational environments in a synergistic and complementary way. This project focused on acquiring a mobile robotic agent platform that can be used to explore these interfaces for a variety of real-world tasks and environments of interest to the Army. It aims to extend our current work, for creating systems enabling mutually-derived situation awareness which use BCI to synergistically couple human expertise and computational intelligence. This DURIP extends this work by providing a test environment where the human control of a robot agent can be experimentally validated in real-world scenarios. The robot platforms used are the Willow Garage PR2 personal robot [21], a humanoid like robot with a mobile omnidirectional base, and a Baxter dual-arm robotic manipulator.

Enter List of papers submitted or published that acknowledge ARO support from the start of the project to the date of this printing. List the papers, including journal references, in the following categories:

(a) Papers published in peer-reviewed journals (N/A for none)

<u>Received</u>	<u>Paper</u>
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TOTAL:

Number of Papers published in peer-reviewed journals:

(b) Papers published in non-peer-reviewed journals (N/A for none)

<u>Received</u>	<u>Paper</u>
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TOTAL:

Number of Papers published in non peer-reviewed journals:

(c) Presentations

Number of Presentations: 0.00

Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Received Paper

TOTAL:

Number of Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Peer-Reviewed Conference Proceeding publications (other than abstracts):

Received Paper

TOTAL:

Number of Peer-Reviewed Conference Proceeding publications (other than abstracts):

(d) Manuscripts

Received Paper

TOTAL:

Number of Manuscripts:

Books

Received Book

TOTAL:

TOTAL:

Patents Submitted

Patents Awarded

Awards

Graduate Students

<u>NAME</u>	<u>PERCENT SUPPORTED</u>
FTE Equivalent:	
Total Number:	

Names of Post Doctorates

<u>NAME</u>	<u>PERCENT SUPPORTED</u>
FTE Equivalent:	
Total Number:	

Names of Faculty Supported

<u>NAME</u>	<u>PERCENT SUPPORTED</u>
FTE Equivalent:	
Total Number:	

Names of Under Graduate students supported

<u>NAME</u>	<u>PERCENT SUPPORTED</u>
FTE Equivalent:	
Total Number:	

Student Metrics

This section only applies to graduating undergraduates supported by this agreement in this reporting period

The number of undergraduates funded by this agreement who graduated during this period: 0.00

The number of undergraduates funded by this agreement who graduated during this period with a degree in science, mathematics, engineering, or technology fields:..... 0.00

The number of undergraduates funded by your agreement who graduated during this period and will continue to pursue a graduate or Ph.D. degree in science, mathematics, engineering, or technology fields:..... 0.00

Number of graduating undergraduates who achieved a 3.5 GPA to 4.0 (4.0 max scale):..... 0.00

Number of graduating undergraduates funded by a DoD funded Center of Excellence grant for Education, Research and Engineering:..... 0.00

The number of undergraduates funded by your agreement who graduated during this period and intend to work for the Department of Defense 0.00

The number of undergraduates funded by your agreement who graduated during this period and will receive scholarships or fellowships for further studies in science, mathematics, engineering or technology fields: 0.00

Names of Personnel receiving masters degrees

NAME

Total Number:

Names of personnel receiving PHDs

NAME

Total Number:

Names of other research staff

NAME

PERCENT SUPPORTED

FTE Equivalent:

Total Number:

Sub Contractors (DD882)

Inventions (DD882)

Scientific Progress

See attached.

Technology Transfer

Not Applicable.

DURIP Final Project Report

Award W911NF-13-1-0292:

Brain Computer Interfaces for Enhanced Interaction with Mobile Robot Agents

Principal Investigator: Peter K. Allen, Columbia University

1 Equipment Purchased

1. PR2 Mobile Robot, Willow Garage, \$175,000.00
2. Baxter Dual-arm robot, Rethink Robotics, \$27,500.00

2 Research Projects Using the Equipment

2.1 Brain Computer Interface for Grasping and Manipulation

Brain Computer Interfaces (BCIs) show great potential in allowing humans to interact with computational environments in a synergistic and complementary way. This project focused on acquiring a mobile robotic agent platform that can be used to explore these interfaces for a variety of real-world tasks and environments of interest to the Army. It aims to extend our current work, for creating systems enabling mutually-derived situation awareness which use BCI to synergistically couple human expertise and computational intelligence. This DURIP extends this work by providing a test environment where the human control of a robot agent can be experimentally validated in real-world scenarios. The robot platforms used are the Willow Garage PR2 personal robot [21], a humanoid-like robot with a mobile omnidirectional base, and a Baxter dual-arm robotic manipulator.

Brain-Computer Interfaces are promising technologies that can improve Human-Robot Interaction. Non-invasive BCI's, which are very desirable from a medical and therapeutic perspective, are only able to deliver noisy, low-bandwidth signals, making their use in complex tasks difficult. To this end, we present a shared control online grasp planning framework using an advanced EEG-based interface that can interface with the PR2 robot to accomplish Human-in-the Loop (HitL) grasping tasks. Unlike commonly used paradigms, the EEG interface we incorporate allows online generation of a flexible number of options. This online planning framework allows the user to direct the planner towards grasps that reflect their intent for using the grasped object by successively

selecting grasps that approach the desired approach direction of the hand. The planner divides the grasping task into phases, and generates images that reflect the choices that the planner can make at each phase. The EEG interface is used to recognize the user’s preference among a set of options presented by the planner. The EEG signal classifier is fast and simple to train, and the system as a whole requires almost no learning on the part of the subject.

Using EEG as the user interface has a number of advantages. Firstly, the neurological phenomena used in the system is a subconscious reaction to visual stimuli, and therefore needs very little user expertise to operate. Secondly, the planner can take advantage of visual ambiguity between functionally similar grasps to achieve fast convergence in the shared-control paradigm. The user acts as a filter for the planner, directing it to a desired approach direction and filtering proposed candidates until a reasonable one is found. Three users were able to use this system with minimal training to pick up a variety of objects in a semi-cluttered scene. Also,, five users were able to use this system to pick up objects in cluttered scenes where object recognition was unable to correctly recognize the complete planning scene, depending instead on the user’s preferences to choose viable grasps. These experiments suggest that the 1) reduced cognitive load of the EEG version of the system allows the subjects to plan grasps in scenes far more cluttered than the EMG version was able to handle, 2) substantially reduces training time over the EMG based system, 3) outperforms the previous version of the EEG and EMG systems in terms of run-time, 4) allows stable grasping amidst clutter and uncertainty, and 5) works across multiple hardware platforms.

2.2 Experimental Results

Figure 1 shows the experimental setup and Figure 2 shows the grasping pipeline we implemented. We performed three experiments using a robotic manipulator and the PR2-based system, using a shared implementation of the EEG/RSVP option selection and the same training procedure.

For the first experiment, we validated the initial robot arm system by asking three subjects to instruct the robot to lift three objects in a typical scene. The results from this experiment show that an RSVP-based Human-in-the-loop planner can effectively be used for grasp planning.

In the second experiment, we asked five subjects to use the PR2-based system to lift the same three objects in a highly cluttered scene, where not all of the objects in the scene were in the object recognition database. In this experiment, the subject provides information that is not available to the planner: in order to plan an effective grasp, the user must ensure that the planner does not choose a grasp which would collide with an unrecognized object. Figure 3 shows this experimental setup and Table 1 shows these results.

In the third experiment, we asked five subjects to pick up objects that were explicitly removed from the object recognition database. In this experiment, we examine the case where the planner is actually given an incorrect view of the world. That is, we set up the object recognition system to mistakenly identify a shaving gel bottle as a shampoo bottle which is both wider and taller, so a large fraction of the suggested grasps will not lead to a successful pickup. In particular, grasps



(a) Robot arm system



(b) PR2 system

Figure 1: (a) Initial testing: The subject guiding a robotic arm through an automated grasping task using EEG BCI. On the left side is the robotic manipulator and three containers in the grasping scene. On the right is a subject using the system through the B-Apert EEG cap, which is relatively unobtrusive and can be worn for long periods of time. In this example, at least one of the grasps found in the database for the object was reachable, and is highlighted in blue in the upper left corner of the grid. The user may choose to execute the highlighted grasp, or to re-seed the planner with one of the other nine grasps and then re-enter the active refinement phase with a new highlighted grasp.

(b) Implementation on PR2 robot: The subject guiding the PR2-based system through the grasp selection phase. On the far left is the subject wearing the B-Apert EEG cap; also on the left is the PR2 robot with its arms posed so as to allow the Kinect mounted on its head a full view of the scene. The user is presented with images of grasps on the screen in the far right. Once one of the grasps is selected, the system will proceed to the grasping stage.

approaching from the top of the shaving cream bottle will almost always fail. This experiment takes advantage of the subject's ability to generalize grasps, recognizing that a subset of the grasps for a mis-identified object may still work in practice. This experiment was conducted on the same five subjects as the cluttered scene experiment with the PR2 during the same test session. Thus, the subjects were experienced with the use of the RSVP paradigm and had become aware that the planner would not necessarily suggest good grasps to the user. Table 2 shows these results. All testing was approved by the Institutional Review Board of Columbia University under Protocol IRB-AAAJ6951.

2.3 Discussion

The results from the two PR2 experiments imply that there are benefits to further leveraging the human's ability to select viable grasps. For example, the current system is dependent on having a set of grasps from a pre-computed grasp database for the initial grasp selection state. This in turn necessitates that computer models exist for all objects to be grasped. Ergo, the system cannot pick up previously unseen objects. However, recent work in 3D shape completion has shown that it is possible to plan grasps on completed meshes, which could result in a system which uses human input to choose viable grasps for unknown objects.

The extension of the online Human-in-the-Loop planner to this EEG based image streaming paradigm has just begun. In its current implementation, the subject decisions are elicited at fixed points of the pipeline. Future work will move towards attempting to integrate the EEG data in a more real-time strategy. We are also beginning new experiments using the Baxter dual-arm robot that entail bi-manual manipulation using the BCI interface. New research we are proposing involves integrating a fNIRS (Functional Near-Infrared Spectroscopy) with the EEG sensing to improve the BCI response.

2.4 Papers and Videos

- Grasping with your Brain: a Brain-Computer Interface for fast grasp selection by Robert Ying, Jonathan Weisz and Peter K. Allen, submitted to Int. Journal of Robotics Research.

http://www.cs.columbia.edu/~allen/ijrr_paper.pdf

- Video of the BCI interface and PR2 grasping:

http://www.cs.columbia.edu/~allen/IJRR_RSVP.mp4

- Video of Virtual Reality Interface to PR2

<https://www.youtube.com/watch?v=5aGuw1Qu6oc>

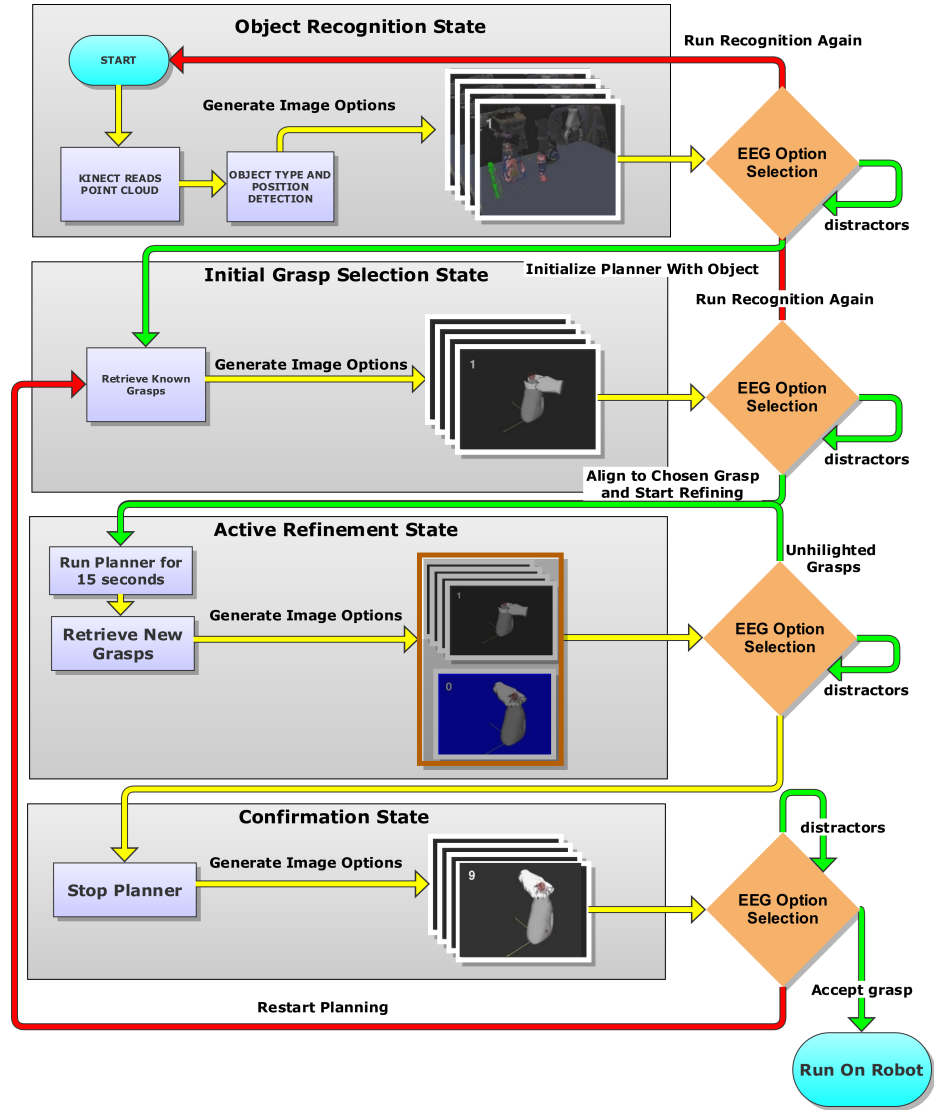


Figure 2: A diagram outlining the EEG RSVP-driven grasping pipeline. In each phase, a series of images is generated representing the available options, and the user can use the RSVP interface to select an option.

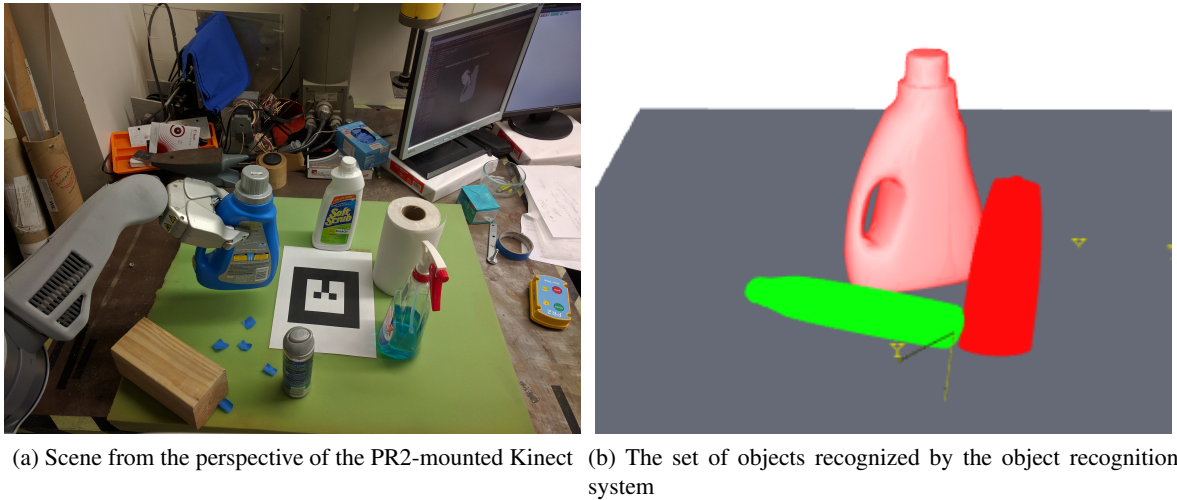


Figure 3: (a) A cluttered scene with many objects and obstacles between the PR2 gripper and the objects in the database, as seen from the perspective of the Kinect mounted on the PR2’s head. Note the large wooden block, which blocks off a large number of possible approach directions for grasps involving the detergent bottle.

(b) The same scene, seen from the perspective of the object recognition system. In this case, the object database contains only the detergent bottle, the shaving gel bottle, and the shampoo bottle, and explicitly excludes a model for the wooden block. It is approximated with the shampoo bottle model, highlighted in green, which does not fully represent the volume occupied by the block.

3 Other Research Work

We have also used the Baxter dual-arm robot in a number of experiments related to grasping deformable objects. Grasping and manipulation of deformable objects presents a host of new research challenges that are much more demanding than for rigid objects. A particular challenge is to fully understand the physics of deformation and to model deformable objects in a way that can be used by real robotic systems in the presence of noise and uncertainty and with real-time constraints. This research uses offline simulation to predict states of deformable objects modeled as thin-shells (i.e. cloth, fabric, clothing) that can then be recognized by a robotic vision/grasping system to pick up and manipulate these objects.

Papers resulting from this research include:

- Yinxiao Li, Chih-Fan Chen, and Peter K. Allen Recognition of Deformable Object Category and Pose, IEEE Int. Conf. on Robotics and Automation(ICRA). Hong Kong, June 2014.

- Yinxiao Li, Yan Wang, Michael Case, Shih-Fu Chang, Peter K. Allen, Real-time Pose Estimation of Deformable Objects Using a Volumetric Approach, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) September 14-18, 2014. Chicago.
- Yinxiao Li, D. Xu, Yonghao Yue, Yan Wang, S-F Chang, E. Grinspun, and P. K. Allen. Regrasping and Unfolding of Garments Using Predictive Thin Shell Modeling Video , IEEE International Conference on Robotics and Automation (ICRA), Seattle, May 2015
- Yinxiao Li, Y. Yue, Danfei Xu, Eitan Grinspun, Peter K. Allen. Folding Deformable Objects using Predictive Simulation and Trajectory Optimization IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) 2015, Hamburg.
- Yinxiao Li, Xiuhan Hu, Danfei Xu, Yonghao Yue, Eitan Grinspun, and Peter Allen, Multi-Sensor Surface Analysis For Robotic Ironing, IEEE International Conference on Robotics and Automation (ICRA), Stockholm, May 2016.

Table 1: Experimental results from five subjects using the PR2 arm in a heavily cluttered scene

Grasp	Subject	Trial	Misselections	Iterations	Successful?	Time (s)
Detergent Bottle Top	1	1	0	1	Yes	70
	1	2	0	1	Yes	80
	2	1	0	2	Yes	85
	2	2	0	1	Yes	85
	3	1	0	1	Yes	70
	3	2	1	1	Yes	85
	4	1	0	1	Yes	80
	4	2	0	2	Yes	95
	5	1	1	2	Yes	105
	5	2	0	1	Yes	95
Detergent Bottle Side	1	1	0	1	Yes	75
	1	2	0	1	No	80
	2	1	0	1	Yes	90
	2	2	0	3	Yes	110
	3	1	1	1	Yes	85
	3	2	0	3	Yes	100
	4	1	2	1	Yes	80
	4	2	0	1	No	85
	5	1	1	1	Yes	95
	5	2	0	1	Yes	75
Shampoo Bottle Top	1	1	1	1	Yes	75
	1	2	0	2	Yes	100
	2	1	0	1	Yes	80
	2	2	0	1	Yes	85
	3	1	1	3	Yes	110
	3	2	0	1	Yes	85
	4	1	0	1	Yes	75
	4	2	0	2	Yes	100
	5	1	1	1	Yes	90
	5	2	0	2	Yes	95
Shampoo Bottle Side	1	1	0	3	Yes	100
	1	2	0	1	Yes	80
	2	1	0	1	Yes	85
	2	2	1	2	Yes	105
	3	1	0	1	Yes	75
	3	2	0	2	Yes	85
	4	1	1	1	Yes	90
	4	2	0	3	Yes	110
	5	1	0	1	Yes	75
	5	2	1	1	Yes	85
Shaving Gel Top	1	1	0	1	Yes	75
	1	2	0	1	Yes	80
	2	1	0	1	Yes	85
	2	2	0	1	Yes	75
	3	1	0	2	Yes	100
	3	2	0	2	Yes	105
	4	1	1	1	Yes	85
	4	2	0	2	Yes	90
	5	1	0	1	Yes	80
	5	2	0	2	Yes	85
Shaving Gel Side	1	1	0	2	Yes	95
	1	2	0	1	Yes	80
	2	1	0	1	Yes	75
	2	2	0	3	Yes	110
	3	1	0	1	Yes	100
	3	2	0	2	Yes	95
	4	1	0	1	Yes	75
	4	2	1	3	Yes	120
	5	1	0	1	Yes	80
	5	2	1	1	Yes	85

Table 2: Experimental results from five subjects using the PR2 arm to pick up mis-identified objects

Grasp	Subject	Trial	Misselections	Iterations	Successful?	Time (s)
Mis-identified Shaving Gel	1	1	0	2	Yes	90
	1	2	0	2	Yes	95
	2	1	0	3	Yes	105
	2	2	0	2	Yes	95
	3	1	0	3	Yes	110
	3	2	0	2	Yes	100
	4	1	0	2	Yes	105
	4	2	0	1	Yes	85
	5	1	0	2	Yes	100
	5	2	0	4	Yes	120